Gait Analysis Based Parkinson's Disease Auxiliary Diagnosis System

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Abstract

Parkinson's disease (PD) is a neurodegenerative disease that often occurs in elderly people. Its symptoms are static tremor and slow movement, which affect the life of the patient seriously. With the development of medical technology, the early diagnosis of PD has attracted widespread attention. Many studies have shown that abnormal gait characteristics are potential bases for judging whether suffering from Parkinson's disease. If PD can be diagnosed in the early stage, it will benefit the control of the disease and subsequent treatment. However, the diagnosis of PD is a complex task which often relies on the doctor's experience and subjective evaluation. In this stage, because of the lack of professional knowledge of doctors or errors in subjective judgment, it is easy to misdiagnose and miss the best treatment time. In response to this problem, this paper designs an auxiliary diagnosis system for PD based on abnormal gait, composed of embedded devices, mobile terminals and servers. The embedded device uses the accelerometer to collect the patient's six-dimensional gait data, then the data are transmitted to the mobile phone via Bluetooth and sent to the server. The server analyzes the data by 1D convolutional neural network model and monitors the abnormality of the patient's gait. Herein, we proved that the use of 1D convolutional neural network for analysis has better performance with five-fold cross-validation, and its recognition accuracy rate reaches 91.4%.

Keywords: Embedded devices, Gait analysis, Parkinson's disease, 1D convolutional neural network

1 Introduction

Parkinson's disease (PD) is a common neurodegenerative disease caused by the progressive loss of dopaminergic and other subcortical neurons [1]. In recent years, the prevalence of PD has shown an upward trend, and over 6 million people worldwide suffer from PD [2]. Besides the symptoms of dyskinesia, PD can also cause non-motor symptoms such as sleep disturbance, depression and constipation [3], which has a great impact on the daily life of patients.

The symptoms that doctors use to evaluate PD include rest tremor, bradykinesia, rigidity and loss of postural reflexes [4]. Many related works of assessing PD by patient actions are reported. Some studies have shown that the handwriting of Parkinson's patients does not show the phenomenon of exercise expectations [5], so there are some studies on handwriting analysis to diagnose PD. Sara Rosenblum used a sensor to measure the average pressure and speed of the subjects when writing, and analyze the characteristics to determine whether the experimenter had PD [6]. Moises Diaz proposed a novel classification model based on one-dimensional convolutions and Bidirectional Gated Recurrent Units (BiGRUs) to assess the potential of sequential information of handwriting in identifying Parkinsonian symptoms [7]. And the proposed method outperformed state-of-the-art approaches on the PaHaW dataset and achieved competitive results on the NewHandPD dataset. However, the experimental process of this method is complicated, and it is necessary to collect all movement data for the entire experiment.

Many studies have shown that abnormality of gait is also a basis for judging whether to have PD [8]. If PD can be diagnosed in the early stage, it will greatly facilitate the control of the disease and subsequent treatment. It can be seen that the early diagnosis of PD is important to guide treatment decision. But the diagnosis of PD is a very complex task, gait assessment as one of the evaluation methods is challenging, which often depends on the experience and subjective evaluation of doctors. In this stage, due to the lack of professional knowledge or subjective judgment error of doctors, it is easy to misdiagnose the disease, resulting in inappropriate treatment, and now there is no objective evaluation index to assist doctors

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to judge whether patients have PD.

Recently, people have done some research on PD detection based on abnormal gait. Xuwei Fan detected the patient's panic gait and freezing of gait (FOG) through linear regression and wavelet transformation [9]. The average detection error of step length is 3.17cm, the sensitivity of fog detection is 90.2%, and the specificity is 88.0%. Marc Bächlin proposed a wearable auxiliary device for gait symptoms of PD patients [10]. This wearable system uses acceleration sensors to measure the patient's movement. It detects FOG by analyzing the frequency components inherent in these movements. When FOG is detected, the assistant will provide rhythmic auditory signals to stimulate the patient to resume walking. Imanne El Maachi uses a 1D convolutional neural network to process signals, and proposes a Parkinson based on Unified PD Rating Scale (UPDRS) The algorithm of disease severity prediction achieves 85.3% accuracy in predicting the severity of PD on the dataset collected by Physionet [11].

Although previous studies have high accuracy for Parkinson's detection, the detection methods are complicated and require multi sensors [12]. Therefore, we designed a Parkinson-assisted diagnosis based on abnormal gait. The system uses fewer sensors to collect gait data, and uses deep learning methods to analyze the data to detect abnormal gait. The main contributions of this work are as follows: We designed a wearable gait data acquisition system so that patients can also collect gait data without the help of a doctor to detect panic gait or FOG gait event. And we designed a method to detect abnormal gait using 1D convolutional neural network, with an accuracy rate of 91.4%, and verified that the performance of the model is better than other models through comparative experiments.

The rest of the paper is organized as follows. Section 2 describes the composition and design method of the Parkinson's auxiliary diagnosis system based on abnormal gait. Section 3 designs comparative experiments and cross-validation experiments to evaluate the performance of the system. In Section 4, we discuss and analyze the system from the experimental results, and propose prospects. Section 5 is a summary of the full paper.

2 Materials and Methods

As shown in Figure 1, Gait Analysis based PD auxiliary diagnosis system consists of three parts: an embedded device for data collection, a mobile terminal for data transmission, and a server for data analysis and processing. The embedded device uses a six-axis accelerometer to collect gait data, and then sends the data to the mobile phone at 10 Hz through the Bluetooth module. The mobile phone then sends the data to the server. The server can analyze and detect the collected gait data faster whether there is any abnormal gait incident. The mobile phone sends the recognition result back to the wearable device. If an abnormal gait event occurs, the embedded device uses rhythmic auditory stimulation to assist in the gait's correction.

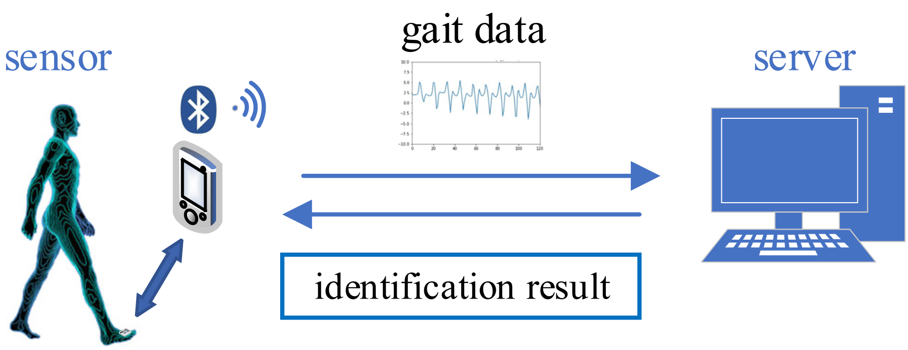

Figure 1. The diagram of PD auxiliary diagnosis system

2.1 Embedded Device

The embedded device is composed of an accelerometer and a Bluetooth module. The accelerometer collects three-axis acceleration data and three-axis angular velocity data of the foot during walking for the subsequent server to analyze the gait. As shown in Figure 2, we can use the sensor when it is fixed on the shoes. We set the person's walking direction as the y-axis to measure the acceleration data and angular velocity data of the experimenter while walking. Since the data is transmitted to the mobile phone through Bluetooth communication, and the original data sent by the sensor is transmitted from the mobile phone to the server, the server needs to analyze the original data to get the gait waveform data.

2.2 Dataset

Using the embedded device we developed, we collected the data of 50 patients with PD and 50 normal subjects in the Department of Neurology, The First Affiliated Hospital of Xiamen University. The data has passed the ethical audit of Xiamen University. 50 Parkinson's disease patients, including 34 males

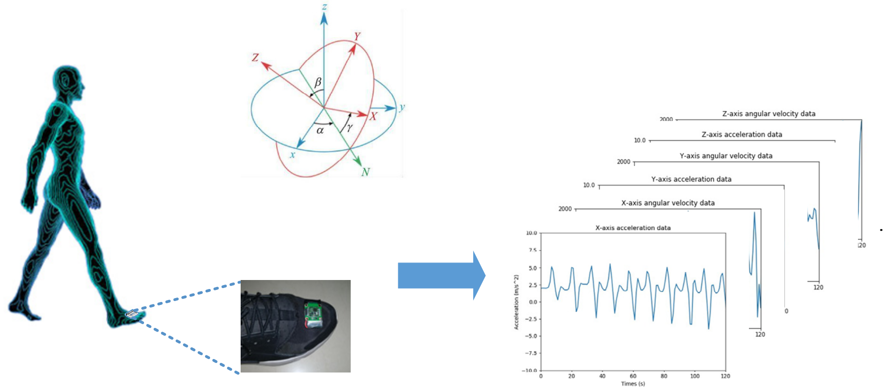

Figure 2. Accelerometer collects data and converts it into gait waveform after processing

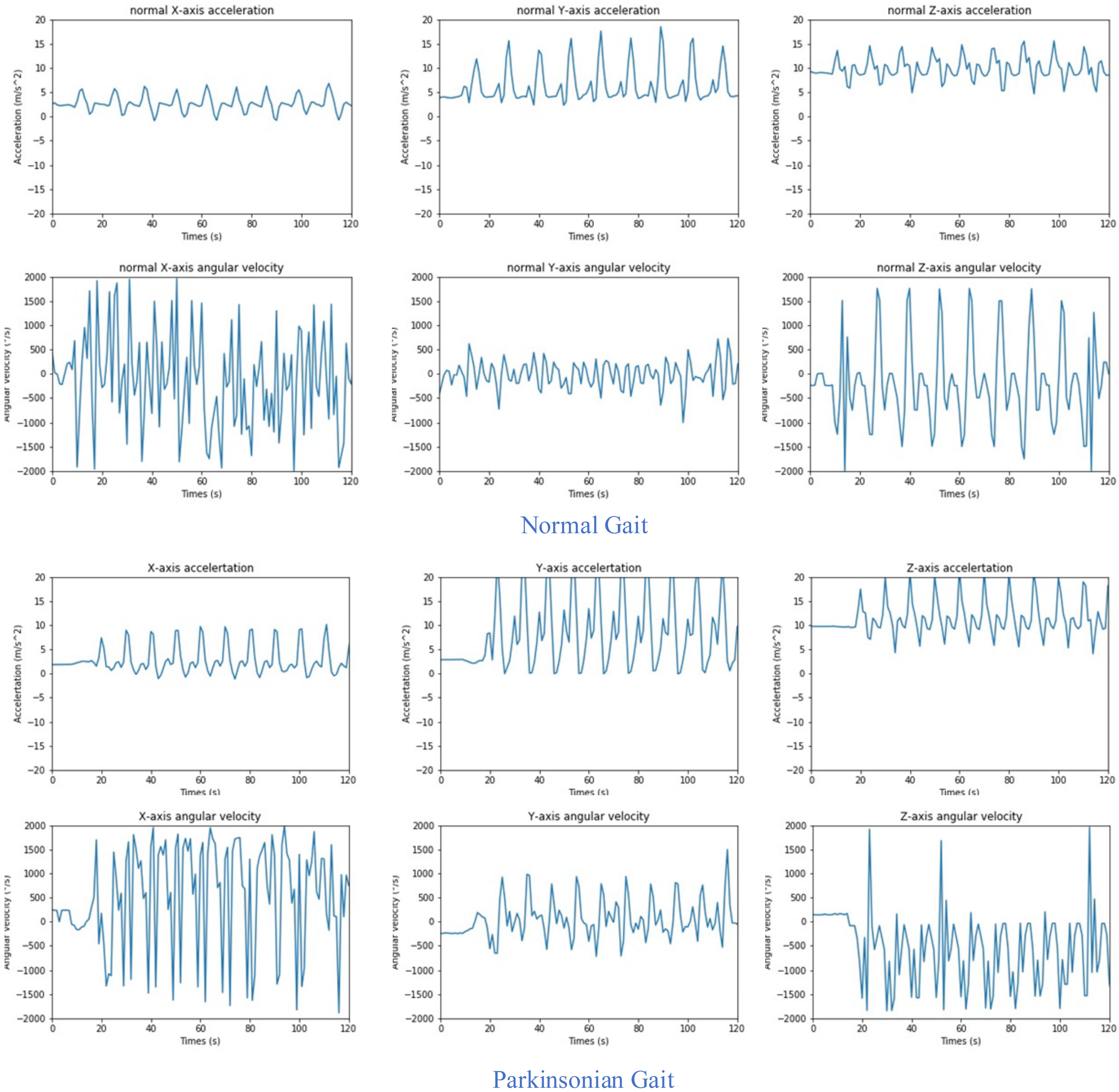

Figure 3. The samples of the waveforms of gait data collected by our system

and 16 females, with an average age of 57.68±6.93 years old, with an average score of 23.87±16.88 in MDS-UPDRS Part III of the "on" stage, and an average of 1.57 in Hoehn-Yahr staging (HY staging) ±0.65 period. All patients meet the PD diagnostic criteria introduced by the International Society for Movement Disorders (MDS) in 2015 [13], and all meet clinically diagnosed PD or likely PD. Subjects voluntarily participate in this study and can cooperate with the collection and scale of clinical data assessment. The subjects are required to keep a uniform pace as far as possible and walk 50 meters along a straight line. Because the packet sending frequency is 10 Hz, according to the different gait frequency of each subject, a subject can collect gait data of 800 ~ 1200 sampling points. As shown in Figure 3 is the waveform of the gait data of the experimental personnel, we can see that the gait data has the characteristics of periodicity.

Comparing the waveform data of Parkinson's patients and normal subjects, each subject has different waveform data because of different walking posture. If we only observe the waveform of gait data intuitively, it is difficult to identify whether the gait data belongs to Parkinson's patients or normal subjects by analyzing the common characteristics of the gait data, so we need to use the deep learning method to help us extract the characteristics of the data. The waveform of each cycle represents a step taken by the wearer. It can be seen that the cycle at the beginning of the waveform may be slightly different from the subsequent periodic waveform because the experimenter has just started to take a step. After collecting the data, we will crop the beginning and end of the gait data, leaving only the middle part.

In order to make the network we designed have better performance, we need to fuse our six-dimensional gait data when making the training set. Since the sensor has different ranges when measuring acceleration and angular velocity, we use the following formula to normalize:

$$\alpha_i' = \frac{\alpha_i}{|\alpha_{i\max}|} \quad i = x, y, z$$

$$\omega_i' = \frac{\omega_i}{|\omega_{i\max}|} \quad i = x, y, z$$

In the formula, $|\alpha_{i\max}|$ and $|\omega_{i\max}|$ represent the absolute value of the range of sensor acceleration and angular velocity. Since our sensor's acceleration and angular velocity ranges are $\pm 160 m/s^2$ and $\pm 2000°/s^2$, $|\alpha_{i\max}|$ is 160 and $|\omega_{i\max}|$ is 2000.

Since our model uses a 1D convolutional neural network, an enormous amount of training data will make the model converge well. Due to the periodic characteristics of gait data, features can be extracted without a long sequence. So we use a time window of length 50 and interval 25 to intercept gait sampling data, and get 1001 segments of data for training and testing models.

After the data preprocessing, we divided the dataset into the training set and validation set. As mentioned above, we use a time window with a length of 50 and a step of 25 to partition gait data. In order to avoid over-fitting, we first divide the data set according to individual subjects, and then use the time window to augment the data of each subject, to ensure the training set, validation set and test set. The sample distribution of the machine is independent.

2.3 1D Convolutional Neural Network

The function of our model is to divide gait data into two categories: abnormal gait and normal gait. The input of the model is a six-dimensional gait sequence, and the output is a binary classification result. The six-dimensional gait sequences are collected by the data embedded device introduced above and obtained after preprocessing. Because the length of the training data sequence is short, no complicated network structure is required. We use the deep learning method to build a simple one-dimensional convolutional neural network with convolutional layer, pooling layer and fully connected layer. Below we also prove through experimental comparison that this method is superior to other classification methods.

It shows the architecture of the model in Figure 4. Our model has four convolutional layers, two pooling layers and two fully connected layers. The convolution layer is composed of several convolution units. The parameters of each convolution unit are obtained by the backpropagation algorithm during training. The purpose of using the convolutional layer is to extract the different features of normal gait, panic gait and FOG by performing convolution operations on the gait sequences. The structure of multiple convolutional layers enables the network to iteratively extract more complex features from the low-level features of gait data. And we use the maximum pooling method in the network. It divides the input sequence into several parts and outputs the maximum value for each part. This mechanism can reduce the dimensionality while preserving the main characteristics of the gait, reducing the network parameters and the amount of calculation, and it also controls over-fitting. We use the Dropout layer to prevent overfitting of neurons during training [14] (omitted in the figure). The fully connected layer integrates all the characteristics and classifies the gait data.

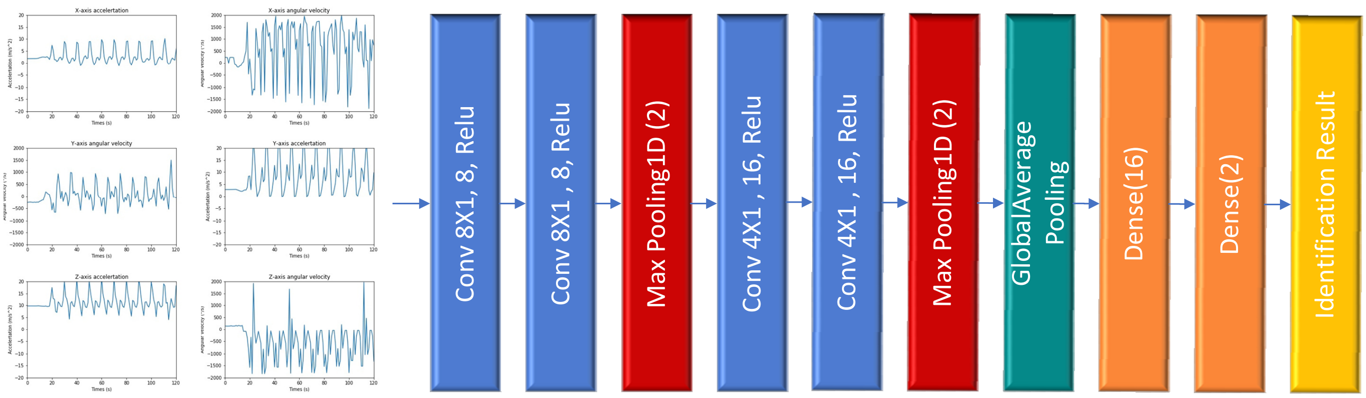

Figure 4. The model structure of the 1D convolutional neural network

We use Softmax as the loss function in the output layer:

$$S_i = \frac{e^{V_i}}{\Sigma_j e^{V_i}}$$

S_i is the Softmax value of an element in an array V, which is equal to the ratio of the exponent of this element to the exponent of all elements in the array. It can be seen from the formula of the Softmax function that it can map the input to a value between (0, 1), and the sum of these values is 1, so the output result of Softmax can also be understood as a probability. In order to enable the network to be trained, we use categorical cross entropy as the loss function, which is defined:

$$L_i = -\log(\frac{e^{f_{y_i}}}{\Sigma_j e^j})$$

f_{y_i} is the output of the correct classification of this set of data, taking the negative logarithm of the Softmax value of this output value as the loss function. If the model classification effect is good, the Softmax value of correct output is larger, and L_i is smaller.

3 Experiments

We use the divided training set to train the network. During training, we use the Adam optimizer to train the network [15], and use a smaller learning rate to train the network. We set the learning rate to 10^-4. In order to test the performance of the network model, we use cross-validation and ROC curve to evaluate the system performance further.

3.1 Cross Validation

Cross-validation is one of the most important methods for statistical analysis, because in practice it is often necessary to verify the stability of a model, that is, the generalization ability of the model on a new data set. In this experiment, we used 5-fold cross-validation to evaluate the performance of the model. We divide our dataset into 5 parts, take 1 of the 5 parts as the validation set to evaluate the model, and the remaining 4 parts are used to train the model, repeat this step 5 times. Five different models can be obtained, and these five models are synthesized to evaluate the performance of our network model.

For the test of this model, our samples are divided into two groups: normal gait or abnormal gait, normal gait is regarded as positive group, and abnormal gait is regarded as negative group. We divide the test results into four categories:

True positive (TP): Normal subjects are correctly classified.

False positive (FP): PD patients are misclassified.

True negative (TN): PD patients are correctly classified.

False negative (FN): Normal subjects are misclassified.

Besides accuracy, we use specificity and sensitivity as the evaluation indicators of our cross-validation experiment, the calculation formula is as follows:

$$Sp = \frac{TN}{TN + FP}$$

$$Se = \frac{TP}{TP + FN}$$

3.2 ROC Curve

The ROC curve is often used to measure the performance of a system, and its meaning is the sensitivity of a system to a certain characteristic. We calculate the True Positive Rate (TPR) and False Positive Rate (FPR) by using true positive, false positive, true negative, and false negative. We draw the ROC curve based on the two data of false negative class rate and true class rate. The calculation formula for false negative class rate and true class rate is:

$$TPR = \frac{TP}{(TP + FN)}$$

$$FPR = \frac{FP}{(FP + TN)}$$

3.3 Comparative Experiment

In order to verify the superiority of our model, we also set up several models as a control group for testing, including Support Vector Machine (SVM), Long Short-Term Memory (LSTM) and the combination of LSTM and convolutional neural networks. The layer descriptions for LSTM and LSTM+CNN are given in Table 1 and Table 2.

Table 1. Layer descriptions for LSTM

Layer no	Layer type	Number of units
1	LSTM	40
2	LSTM	20
3	Dense	20
4	Dense	2

Table 2. Layer descriptions for LSTM+CNN

Layer no	Layer type	Number of units	Kernel size
1	1D Convolutional	8	8
2	1D Convolutional	8	8
3	Max-pooling	-	2
4	1D Convolutional	16	4
5	1D Convolutional	16	4
6	Max-pooling	-	2
7	LSTM	20	-
8	Dense	20	-
9	Dense	2	-

Support Vector Machines (SVM) is a two-category model. The learning strategy of SVM is to maximize the interval which can be formalized as a problem of solving convex quadratic programming. It is also equivalent to the problem of minimizing the regularized hinge loss function [16]. Compared with neural network, SVM has better generalization and promotion ability. We are interested in the classification ability of SVM on gait data, so we also set it as a control group.

Long Short-Term Memory (LSTM) is a special type of time loop neural network that can learn long-term dependent information. LSTM was proposed by Hochreiter in 1997 [17] and was recently improved and promoted by Alex Graves [18]. It solves the problem of long-term dependence through deliberate design. In many practical problems, LSTM has achieved considerable success and has been widely used.

The combination of LSTM and convolutional neural networks is proposed by Ming Tan [19]. Its function is the combination of the two, extracting the key semantics of the text, and then extracting the key features of the semantics. This method is often used for gait analysis in PD [20-22]. Since we use a 1D convolutional neural network as a model, we want to know through experiments whether the increase of the LSTM part will improve the performance of the network.

4 Results & Discussion

4.1 Results of the Experiment

Table 3 and Figure 5 is the result of training using a one-dimensional convolutional neural network. As the training time increases, it can be seen that the loss and accuracy of the network tend to be stable and show better convergence. The accuracy of the validation set also increases with the increase in the number of training rounds. It shows that the network has no over-fitting phenomenon. We use a 1D convolutional neural network trained for 120 rounds to cross-validate the data set. When dividing the data set, we should also follow the above criteria, first divide according to the experimenter, and then use the time window to intercept the data to ensure that the training set and the test set do not have data from the same subject.

Table 3. Cross-validation results for PD identification

	Sp(%)	Se(%)	Acc(%)
1	83.0	92.7	87.5
2	100	90.2	94.4
3	97.1	90.2	93.4
4	92.3	92.7	92.5
5	86.3	94.7	88.7
Average	91.7	90.1	91.4

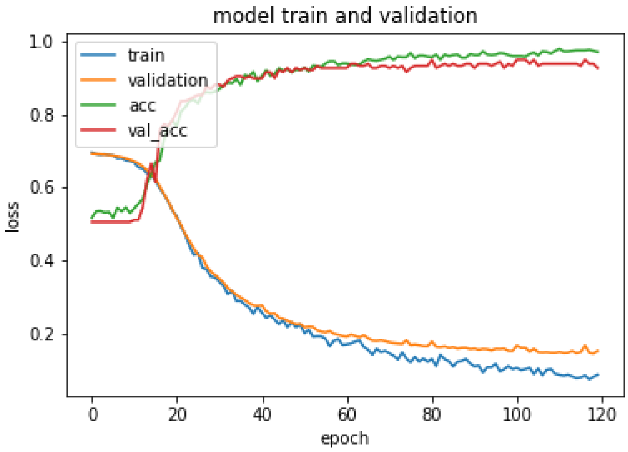

Figure 5. Training loss function and accuracy curve

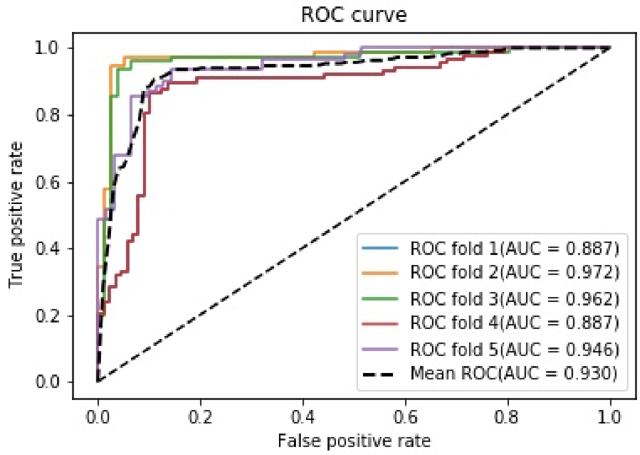

Figure 6. ROC curve and AUC value

Figure 6 is the result of calculating the AUC value of the ROC curve. The AUC values of the five cross-validation results are all greater than 0.85, and the average AUC value is 0.930, showing that the classification model has good generalization performance. This method can correctly identify the abnormal gait of Parkinson's patients.

It can be seen from Table 4 that the performance of using 1D convolutional neural network is significantly better than the other three methods. Although its performance in specificity is not the best, the 1D convolutional neural network shows a good classification effect on the gait data we collected. The LSTM and LSTM+CNN methods may be more suitable for identifying long time intervals and delays in the sequence, and the gait data we used are all sequences of shorter length, so these two methods did not perform well. The SVM classifier also shows a worse classification performance, because it is difficult to find the kernel function and parameters suitable for the distribution of gait data.

Table 4. The performance comparison of several algorithms

Algorithm	Sp(%)	Se(%)	Acc(%)
1D CNN	91.7	**90.1**	**91.4**
SVM	85.4	70.3	75.2
LSTM	86.5	78.0	83.3
LSTM+CNN	**94.6**	82.9	88.5

4.2 Discussion

In the testing stage, we found that when using the device, if the user stands still, the sensor will collect almost stationary waveforms. Such data with a large difference from the gait data will cause the system to misidentify. Therefore, we set a certain threshold for the gait analysis of the system. The embedded device is set to analyze and detect gait data only when it detects that the user is walking.

As seen from the test results of the above question, we use the 1D convolutional neural network model, the recognition accuracy of abnormal gait is 91.4%, the specificity is 91.7%, and the sensitivity is 90.1%. Both cross-validation experiments and ROC curves can prove that the system can achieve a better detection effect of Parkinson's symptoms. The identification accuracy of our model needs to be improved compared to other gait-based Parkinson's detection studies. The main reason is that we only collected 50 Parkinson's gait data for the time being. We will continue to use our development in the next step. The device collects gait data of Parkinson's patients and normal people. As the amount of data increases, the accuracy of the model will also improve. We have published the data set we collected, and the data set is published in https://github.com/CFZ87983698/Dataset-for-Gait-Analysis-based-Parkinson-s-disease-auxiliary-diagnosis-and-treatment-system.

Compared with other systems, the system we developed is more convenient to use. The user's gait data can be detected by wearing the embedded device on the shoes. Other studies often place sensors in multiple positions on the legs or wear multiple wearable devices to collect data. Although the identification accuracy is high, the method of using devices is complicated, which is not conducive to the daily life of potential Parkinson patients use.

The Parkinson's auxiliary diagnosis system based on abnormal gait that we designed realizes the collection of gait data with embedded equipment, and accurately detects abnormal gait by analyzing the gait data, which provides help for the early diagnosis of PD. While assisting doctors in diagnosing PD, the system also avoids accidents of PD patients for abnormal gait.

In the next stage, we plan to collect more

Parkinson's patients and normal data, establish a data set with more data, and improve the recognition accuracy of the model. We plan to design a complete set of sup-porting software for the system on the mobile and computer terminals for use by potential Parkinson's patients and doctors. We believe that this system can better assist in the diagnosis of PD in the future.

5 Conclusions

Diagnosis of PD is still challenging. In recent years, the early diagnosis of PD by abnormal gait has attracted widespread attention. The Parkinson's auxiliary diagnosis system based on abnormal gait proposed in this paper collects the user's gait data with an embedded device and transmits the data to the server through Bluetooth. The server uses a 1D convolutional neural network to detect whether the gait is abnormal. The identification accuracy of our system has reached 91.4%. In addition, the system is portable and easy to operate. It can be a practical tool to help potential patients with PD to detect whether they have signs of PD by gait, and to assist patients in correcting their gait.

Acknowledgements

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Biographies

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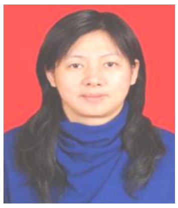

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